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A Neural Network-Based Estimator for the Mixture Ratio of the Space SHUTTLE Main Engine

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The word "Station" should be replaced with "Shuttle" on the cover so that the title reads:

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ABSTRACT

In order to properly utilize the available fuel and oxidizer of a liquid propellant rocket engine, the mixture ratio is closed loop controlled during mainstage (65% - 109% power) operation. However, because of the lack of flight-capable instrumentation for measuring mixture ratio, the value of mixture ratio in the control loop is estimated using available sensor measurements such as the combustion chamber pressure and the volumetric flow, and the temperature and pressure at the exit duct on the low pressure fuel pump. This estimation scheme has two limitations. First, the estimation formula is based on an empirical curve fitting which is accurate only within a narrow operating range. Second, the mixture ratio estimate relies on a few sensor measurements and loss of any of these measurements will make the estimate invalid. In this paper, we propose a neural network-based estimator for the mixture ratio of the Space Shuttle Main Engine. The estimator is an extension of a previously developed neural network-based sensor failure detection and recovery algorithm (sensor validation). This neural network uses an autoassociative structure which utilizes the redundant information of dissimilar sensors to detect inconsistent measurements. Two approaches have been identified for synthesizing mixture ratio from measurement data using a neural network. The first approach uses an autoassociative neural network for sensor validation which is modified to include the mixture ratio as an additional output. The second uses a new network for the mixture ratio estimation in addition to the sensor validation network. Although mixture ratio is not directly measured in flight, it is generally available in simulation and in testbed firing data from facility measurements of fuel and oxidizer volumetric flows. The pros and cons of these two approaches will be discussed in terms of robustness to sensor failures and accuracy of the estimate during typical transients using simulation data.

INTRODUCTION

To assure reliable operation of a complex dynamic system such as the Space Shuttle Main Engine (SSME), redundant sensors are used for measuring critical variables. The redundancy makes it possible to validate measured data, identify a sensor failure, and recover a measurement. Previous studies on the sensor failure detection and accommodation using analytically redundant sensor information can be found in [1,2,3]. The basic idea is to identify the sensor measurement which is not consistent with the others. Once the situation is identified, the failed sensor measurement is replaced by an estimated value generated by a model [1] or by a neural network [2,3]. The autoassociative neural network sensor validation technique proposed in [3] has been very effective for the variables directly measured.

In the SSME operation, one of the important performance parameters, combustion mixture ratio, is not directly measurable. The current controller uses an empirical formula to estimate it. There are two problems with this practice. First, the sensors used to calculate the mixture ratio all become critical in the closed loop operation; a loss of any one of these sensors can lead to a loss of the control of the engine. Second, the empirical estimation of the mixture ratio is only accurate within a narrow range of operation.

In this paper, we present a new estimator for the mixture ratio using neural networks. The neural mixture ratio estimator is designed to be able to accommodate sensor failures and provide accurate estimates across a wide range of operation. In this study we take advantage of the fact that the actual mixture ratio, although not available in the flight operation, is readily available in the testbed firing data. The actual mixture ratio information is also available in our digital simulations of the SSME (Digital Transient Model or ADSIM model) [4]. This study uses the simulation data generated by the SSME real-time model running on an AD100 computer to test the feasibility of the proposed mixture ratio estimator.

RECOVERY OF CRITICAL MEASUREMENTS

In previous studies [2,3], feedforward neural networks with sigmoidal activation functions have been used in sensor validation for a select group of sensors in the SSME flight instrumentation. There are two approaches to sensor validation using neural networks. The first scheme is a two-step approach. A detection neural network is first used to detect the sensor which is not consistent with other sensors and another group of networks is used to recover the

measurements of the failed sensors. The second scheme utilizes one autoassociative neural network with detection logic to do the sensor failure detection and isolation. Accommodation is achieved by feeding back the estimated sensor values to replace the faulty measurements. These two approaches have been successful for sensor validation in both simulation and hot fire data. In these two studies, a group of sensors was selected because of the known interdependency between its members. These sensors also cover the critical information that is used in the control of the SSME during mainstage. The selected sensors are:

P6:	Main Combustion Cooling Pressure
T6:	Main Combustion Cooling Temperature
Qffm:	Low Pressure Fuel Pump exit flow, in volume
Pfd1:	Low Pressure Fuel Pump exit Pressure
Tfd1:	Low Pressure Fuel Pump exit Temperature
Pfd2:	High Pressure Fuel Pump exit Pressure
Sf1:	Low Pressure Fuel Turbopump Speed
Sf2:	High Pressure Fuel Turbopump Speed
Pc:	Main Combustion Chamber Pressure

The current SSME operation requires the control of the thrust and combustion mixture ratio. Engine thrust is controlled by the regulation of Pc (combustion chamber pressure) which is directly related to the engine thrust. The combustion mixture ratio is the ratio of mass flows of oxidizer and fuel, neither of them is directly measured in the flight configuration. The Block-1 controller (as in the current SSME configuration) uses the following equations to estimate the mixture ratio:

$$\rho_H = (k_1 + k_2 P_{fd1}) \times (T_{fd1})^2 + (k_3 + k_4 P_{fd1}) \times T_{fd1} + k_5 + P_{fd1}$$

$$DW_H = k_6 \times Q_{ffm} \times \rho_H$$

$$C2 = k_7 \times (P_c)^2 + k_8 \times P_c + k_9$$

$$MR_E = \frac{(P_c + k_{10})}{C2 \times DW_H} - 1$$

where P_c , P_{fd1} , T_{fd1} and Q_{ffm} are the sensor measurements defined in the previous section, ρ_H is the estimated density of the fuel, DW_H is the calculated fuel mass flow, $C2$ is the coefficient used in the estimation of the oxidizer flow based on the chamber pressure measurement. MR_E is the estimated mixture ratio of the combustion process, and $k_1 - k_{10}$ are constants.

Since all four sensor measurements used in the mixture ratio estimation are covered in the previous sensor list from the sensor validation studies, it can be assumed that the mixture ratio can be recovered during a sensor failure. However, the estimated mixture ratio may not accurately reflect the actual combustion mixture ratio because of the limitation of the empirical estimation formula. Luckily, in the testbed firing, the true mixture ratio information can be accurately calculated because of the extra instrumentation such as the oxidizer flow meter. Also, in the computer simulation, the theoretical value of the mixture ratio is readily available. It is the goal of this study to construct a mixture ratio estimator that is accurate across a wide range of operation and robust to sensor failures.

NEURAL NETWORK ESTIMATORS

In the building of a neural network estimator for the mixture ratio of the SSME, there are two approaches identified. The first approach expands the existing sensor validation network to cover an additional output for the estimation of the mixture ratio. During the course of the study, it was found that the additional information of two control valve positions — Fuel Preburner Oxidizer Valve (FPOV) and Oxidizer Preburner Oxidizer Valve (OPOV) — are important in the estimation of the mixture ratio. The neural network in Figure 1 shows the construction of the approach. In Figure 1, S1 to S9 represent the nine sensors selected in the previous studies and O1 to O9 represent their estimates respectively. The two additional inputs are OPOV and FPOV positions, and the additional output is the mixture ratio estimate. The training data were generated from the real-time SSME simulation for the start-up and down-thrust part of the mainstage operation. It should be noted that the major part of the start-up operation is under open loop control while mainstage operation is closed loop controlled on chamber pressure and mixture ratio. The actual mixture ratio used in the training is defined as the theoretical value of the ratio between oxidizer mass flow and the fuel mass flow.

The second approach is to use a separate neural network solely for the mixture ratio

estimation. This is similar to the chamber pressure recovery network described in a previous study [2]. Again, two valve positions as well as the originally selected sensor measurements are used to estimate the actual mixture ratio. Figure 2 shows the setup of this network in addition to the sensor validation neural network. The network used here has an input layer with 11 nodes, two hidden layers with 20 nodes each and an output node for the mixture ratio estimate.

In this study, the training set of the neural network is generated by the dynamic simulation of the SSME on the AD100 computer. The data include start-up transient, the 100% operation and a portion of the down-thrust operation. The back propagation algorithm is used to adjust the weights of the neural network connections. The training procedure is as follows:

- (1) randomly select one data set from the training data sets,
- (2) randomly select several (number between 0 and 4) failed sensors among S1 to S9,
- (3) for each failed sensor select a random value (between 0 and 1) as the input to the neural network to simulate the failed condition of that sensor,
- (4) use the back-propagation algorithm to adjust the weights so that the output of the network will match the desired parameters.
- (5) repeat steps (1) to (4) until the network converges.

The randomization of the training process has been very effective in the training of a robust estimator that will be insensitive to the sensor failure condition.

SIMULATION RESULTS

Case 1: Expansion of the Sensor Validation Network

In this case, there are 11 inputs to the neural network: 9 sensor measurements and 2 valve positions; and 10 outputs: 9 estimates for corresponding sensor measurements and a mixture ratio estimate. After the training, the network was tested for the simulated condition that there are sensor failures while the engine is going through the max-Q operation where engine thrust is reduced to 65% for a period of time during the mainstage operation before it returns to 100% power operation. The sensor failures selected for testing in this case are the failures of Pc and Qffm. Under the current SSME practice, these two sensor failures will make it impossible for the current controller to perform because of the loss of the required information. Figure 3 and 4 show the results of the neural network recovery of these failed sensors. Figure 5 shows the comparison of the neural network mixture ratio estimate and the estimated mixture ratio used by

the Block-1 controller during the tested condition. The Block-1 controller calculation uses the actual sensor data before any sensor failure and uses the estimate from the neural network instead of the faulty data once a failure is detected. It should be noted that the "theoretical" mixture ratio used here is the mass flow ratio of the oxidizer and the fuel in the real-time simulation which may not be the "actual" combustion mixture ratio in the combustion chamber. It can be seen that the neural network provides a fairly reasonable estimation during these sensor failure conditions while the Block-1 controller estimation is very sensitive to any sensor failure and also sensitive to the error in the estimated values provided by the sensor validation network.

Case 2: Separate Network for Mixture Ratio Estimates

Here, along with the previously defined autoassociative neural network which has 9 inputs and 9 outputs, a second neural network with 11 inputs (9 sensor measurements and 2 valve positions) and 1 output (the mixture ratio estimate) was used. The training data were the same as those used in case 1. After the training, the network was also tested for the max-Q operation with sensor failures as in case 1. Figure 6 shows the comparison of the neural network mixture ratio estimate and the calculated mixture ratio used by the Block-1 controller during the tested condition. Again, it is easy to see that the neural network estimator can provide an accurate estimate of the mixture ratio while maintaining its validity during the period required for the sensor failure detection and recovery.

CONCLUSIONS

Neural networks are proposed to provide mixture ratio estimates that are accurate across the range of operation and remain valid even with some of the sensors failed. The autoassociative neural network used in a previous study to provide the basic network for sensor validation (failure detection and recovery) was extended. Two approaches to extend the sensor validation network were employed. The first approach was to increase the number of inputs to include the valve information and add a network output to cover the estimation of mixture ratio. The second approach was to build a separate network for mixture ratio estimation and use the original network purely for sensor validation. The results show that both approaches performed reasonably well under the test conditions. However, the second approach (separate network) provides a slightly better estimate on the max-Q down thrust operation.

Future research includes the extension of the neural network to cover more measurements

from the oxidizer side of the engine in order to provide more related information for mixture ratio estimation, and to test the neural network estimator during closed loop control.

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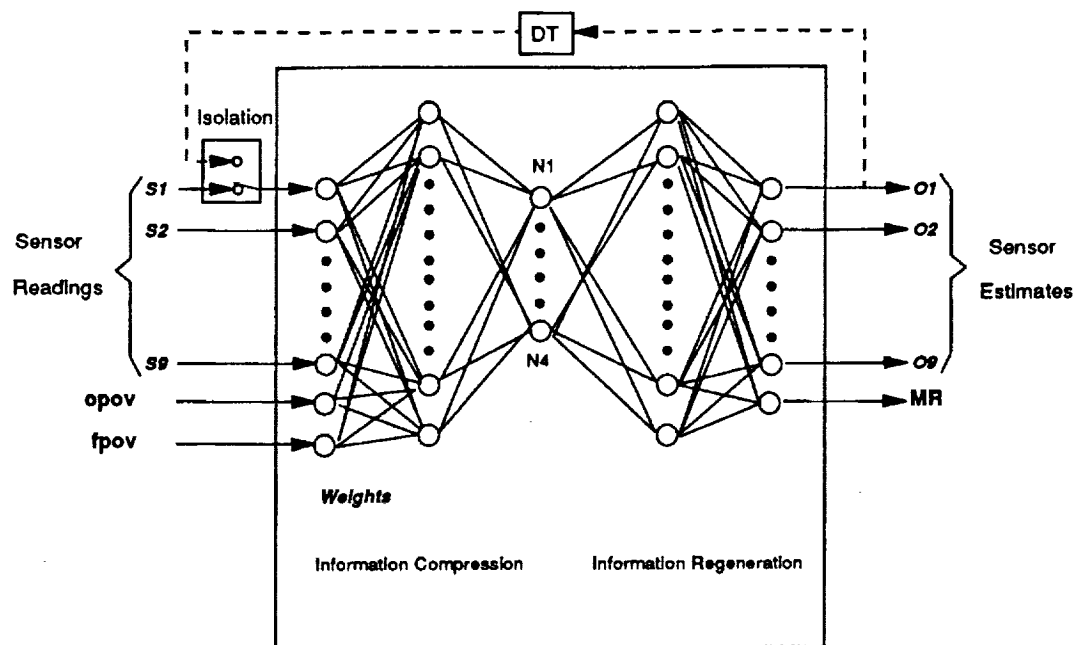


Figure 1. One Neural Network for Sensor Validation and MR Estimation

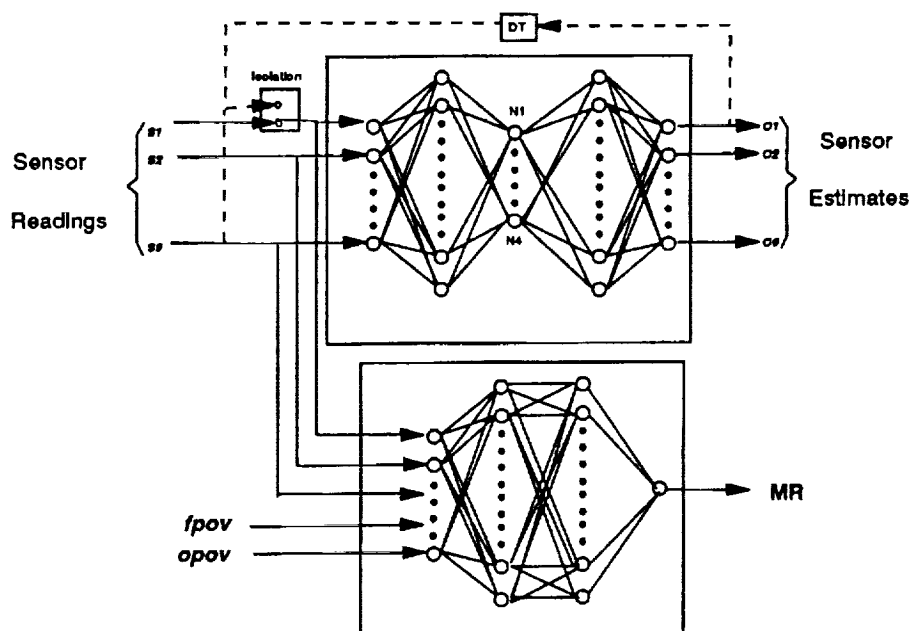


Figure 2. Neural Network Based MR Estimator and Sensor Validation

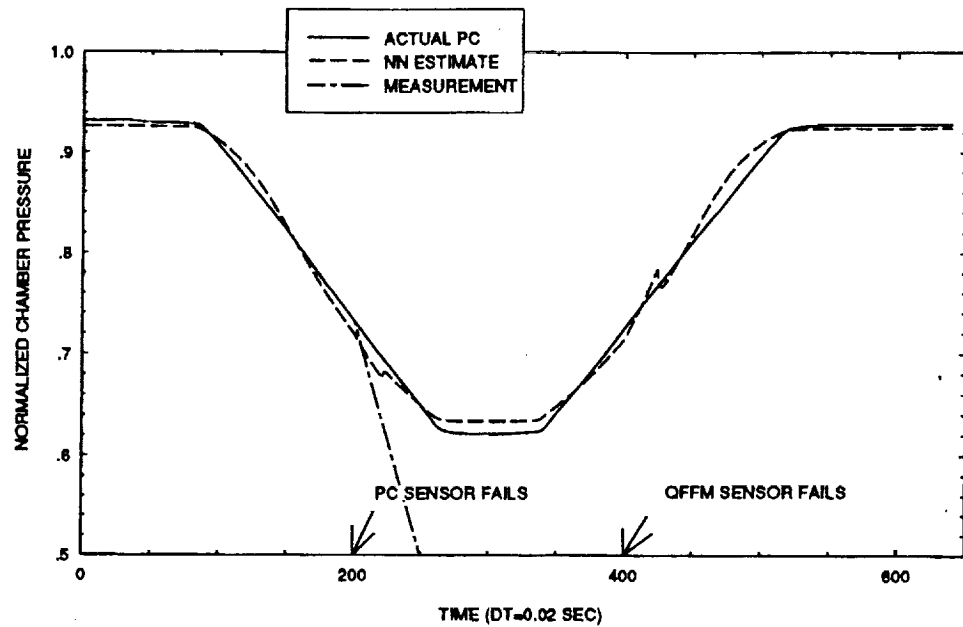


Figure 3. Recovering Chamber Pressure in Case 1

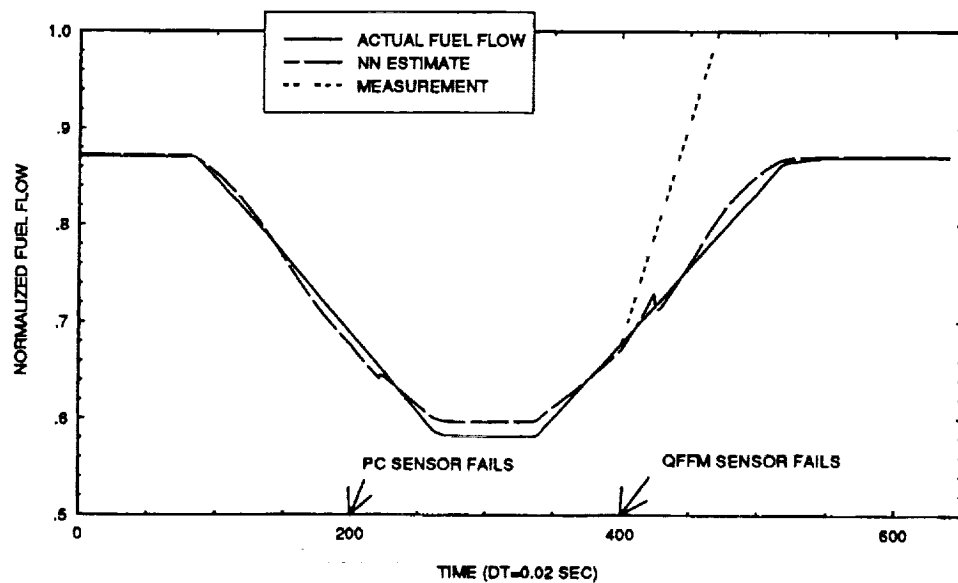


Figure 4. Recovering Fuel Flow in Case 1

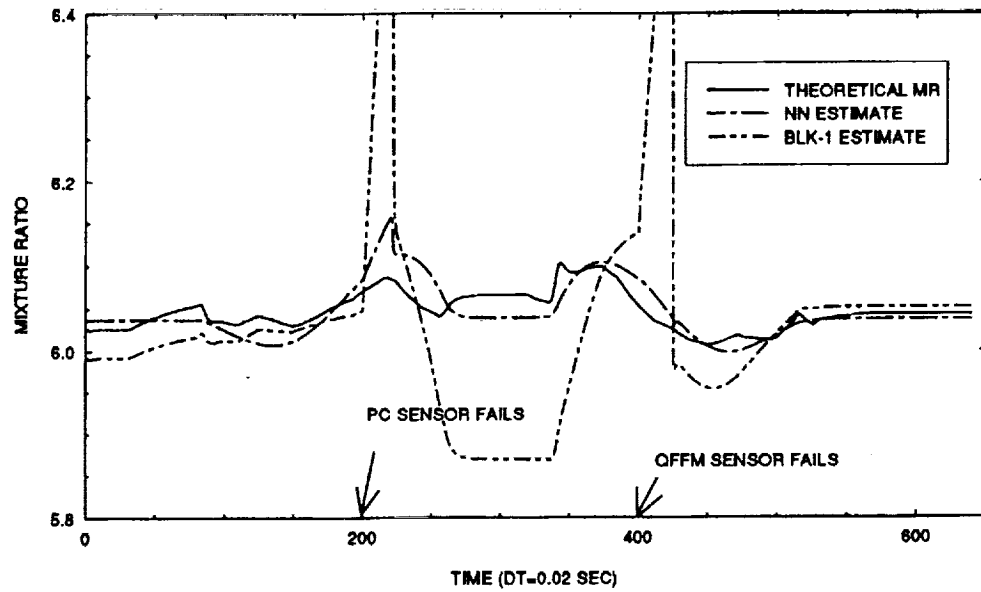


Figure 5. Mixture Ratio Estimation in Case 1

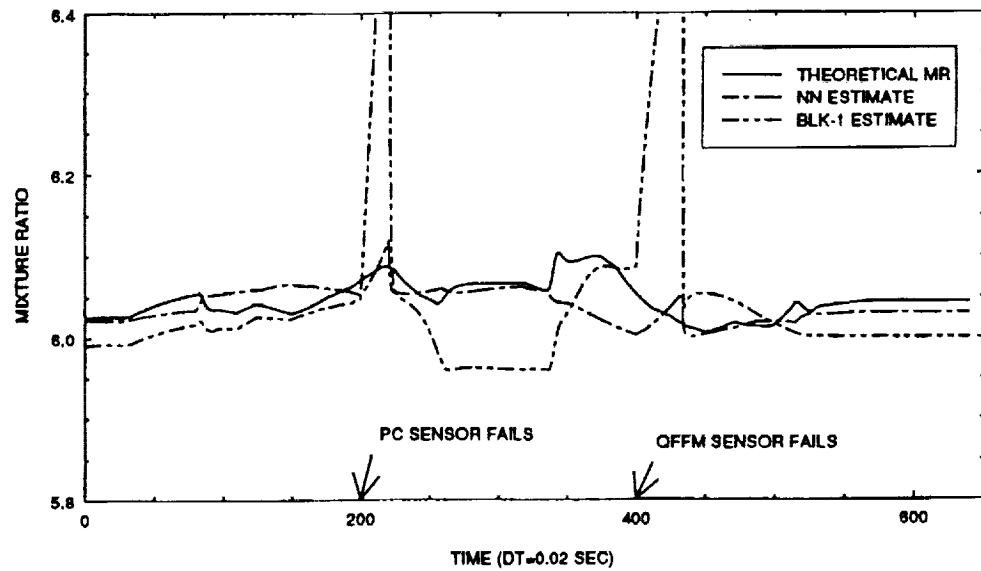


Figure 6. Mixture Ratio Estimation in Case 2

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